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The effects of climate variability on psychological well-being in India

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ABSTRACT

Climate variability has been shown to have adverse effects on morbidity and mortality. Less is known about its effects on psychological well-being, especially in developing countries with agriculture-based economies. In this paper, we test whether extreme temperature and precipitation in India have an effect on self-reported depression symptoms, cognitive and sleep difficulties, and ability to cope with and control life. We use time and geographic variation in weather and show that hot weather in the previous year worsens psychological well-being among rural, but not urban, Indian adults. We examine potential mechanisms and show that the effect is largely driven by hot temperatures during the agricultural season and could be partly attributed to a reduction in agricultural production. We further provide suggestive evidence that the effects of weather shocks could be mitigated with poverty reduction programs such as India's National Rural Employment Guarantee Scheme. Poor mental health has been associated with low productivity and high healthcare expenditures and is a serious concern in India and many developing countries. The adverse impacts of climate change on rural, agriculture-based economies such as India are likely to increase over time. Given that nearly half of the global population lives in rural areas and is vulnerable to climate variability, understanding the effects of climate on psychological well-being and identifying potential resolutions is critical for insuring vulnerable populations and breaking the poverty cycle.
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1. Introduction

Climate change is leading to higher temperatures around the globe and increasingly erratic weather patterns. The Intergovernmental panel on climate change (IPCC) estimates that the global temperature will increase by more than 1.5 °C by the end of the 21st century relative to 1850–1950 temperatures (IPCC, 2014). Extreme heat has adverse effects on morbidity and mortality, increasing vector-borne diseases and cardiovascular problems (Dell, Jones, & Olken, 2012). It also increases aggression (Anderson, Anderson, Deneve, Flanagan, & Door, 2000) and raises violent suicide rates (Lin, Chen, Xirasagar, & Lee, 2008; Maes, Demeyer, Thompson, Peeters, & Cosyns, 1994). In addition, erratic climate patterns influence individuals' beliefs about future weather fluctuations, increasing anxiety and distress in anticipation of future threats (Fritze, Blashki, Burke, & Wiseman, 2008). Climate variability can also worsen psychological well-being by affecting agricultural production and livelihoods, creating economic and social insecurity (Berry, Bowen, & Kjellstrom, 2010).

While the potential impacts of climate variability on psychological well-being have been identified, there is little rigorous empirical evidence for these effects (APA, 2009; Berry et al., 2010). Much of the existing literature tends to focus on acute traumatic events such as typhoons or hurricanes, and uses qualitative approaches to assess extreme weather effects. To address this gap, we use survey data from the World Health Survey (WHS) and the Study on global AGEing and adult health (SAGE) to examine the effects of weather fluctuations on the psychological well-being of Indian adults. We take advantage of time and geographic variation and use a generalized difference-in-differences model to test whether higher frequencies of extreme temperature and precipitation (in terms of deviations from the long-run average) are associated with higher rates of depression symptoms, cognitive and sleep difficulties, and self-reported inability to cope with life and control the important things in life.

The effects of climate extremes are not uniform. Developing countries with agriculture-based economies, large poor populations, and weak institutions may be less able to manage the stresses associated with climate variability than their wealthy, industrialized counterparts (Dell et al., 2012; Mudaliar & Rishi, 2012). In 2005, 55% of total employment in India was in agriculture, and close to 19% of Indian GDP was from agriculture.[1] Burgess, Deschenes, Donaldson, and Greenstone (2014) using

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[1] World Development Indicators, http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators.

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historical data from 1957 to 2000, show that hot and dry weather in India decreases agricultural output and wages. Mahajan (2017) extends this analysis to demonstrate differential wage impacts by gender. Similarly, Guiteras (2007) predicts that the projected change in climate between 2010 and 2039 will reduce major crop yields in India by 4.5–9 percent, imposing substantial economic costs on farmers.

These weather shocks are likely to harm psychological well-being. Carroll, Frijters, and Shields (2009) find that drought conditions during Australian growing seasons significantly reduce life satisfaction among rural populations. Chemin, Laat, and Haushofer (2013) show that negative income shocks, resulting from low rainfall in the preceding year, increase cortisol levels and self-reported stress of Kenyan farmers. Similarly, Carleton (2017) demonstrates that higher temperatures during the agricultural growing season significantly increase annual suicide rates of Indian farmers, and provides supporting evidence that climate effects operate through economic channels.

The effects of climate variability on psychological well-being have important economic and social implications. Psychological distress and depression have been associated with low labor force participation and high healthcare utilization, and may pose a substantial burden on households creating cycles of poverty (Lund et al., 2011). Similarly, agency, the feeling of being able to control the important things in life, has been shown to affect individual education and labor market outcomes (Almlund, Angela Lee, James, & Kautz, 2011; Krishnan & Krutikova, 2013). Finally, stress affects both cognitive capacity and executive control, compromising individuals' economic decision making (Haushofer & Fehr, 2014; Schilbach, Schofield, & Mullainathan, 2016).

Poor mental health, and its economic consequences, are a serious concern in India. One study found that the lifetime prevalence of common mental disorders in Goa was 46% (Patel, Araya, De Lima, Ludermir, & Todd, 1999). Another study of ultra-poor households in Andhra Pradesh found that 35% of households felt anxious or depressed in the previous year (Ravi & Engler, 2015). While there may be a biological basis for depressive symptoms, changes in the environment also matter (Quidt & Haushofer, 2016). Given India's vulnerability to climate change, and the potential burden of mental distress on economic and health outcomes, it is important to understand the effects of climate variability on the psychological well-being of its population.

This paper shows that the number of months with warmer than usual temperatures (higher than one standard deviation above the long-term average) in the previous calendar year have a significant negative effect on psychological well-being, increasing cognitive and sleep difficulties, as well as feelings of being unable to cope with or control the important things in life. The effects of extreme precipitation are weaker and less consistently significant; the effects of temperature are strong and robust to controlling for extreme precipitation. Examining heterogeneity by area of residence, we find that temperature fluctuations primarily affect rural populations, and have no effect on urban residents. Splitting annual temperature and precipitation measures into six-month indicators, roughly corresponding to the agricultural and non-agricultural seasons, we find that the effects of hot temperatures on rural populations are explained by temperatures during the agricultural season in the latter half of the year. We then show that high agricultural-season temperatures are associated with lower agricultural output and diminished physical health, suggesting two potential mechanisms through which climate may affect psychological well-being: income shocks, which create economic uncertainty, and consumption shocks, which affect physical health and impact mental health indirectly. We further explore the potential role of poverty alleviation programs in moderating the effects of income shocks on psychological well-being by examining the effect of India's National Rural Employment Guarantee Scheme (NREGS) – a workfare program – and find that such programs could mitigate some of the distress caused by climate-induced economic hardship.

The paper proceeds as follows. Next, we describe the data and sample used for analysis. Then, in Section 3, we present the identification strategy and empirical specification. Section 4 presents the results of the main analysis, while Section 5 discusses potential mechanisms. We test whether India's workfare program is successful in insuring against climate variability in Section 6. Section 7 concludes.

2. Data

2.1. Household-survey data

This paper uses data from the World Health Survey (WHS) and the Study on global AGEing and adult health (SAGE). The WHS took place in 2003 in six Indian states (Assam, Karnataka, Maharashtra, Rajasthan, Uttar Pradesh and West Bengal), selected to be nationally representative. A cohort of WHS respondents over 50 years of age was interviewed again during the 2007 SAGE survey. While the WHS interviewed one adult from each household, the SAGE survey included additional older respondents from the same households to account for future attrition due to mortality. A sample of 4600 younger adults (18–49) from participating WHS survey households was also included in 2007; this sample specifically targeted women because of a nested study, which aimed to examine women's reproductive health. In some cases, non-WHS households from the same primary sampling units (psus) were included in the 2007 SAGE sample and several new psus were added (Arokiasamy, Sulabha, Sekher, & Lhungdim, 2013). Psus in rural areas are villages, while psus in urban areas are city wards. In this study, we restrict the sample to psus that are available in both years (371 of them). The final sample includes working-age adults (between the ages of 18 and 60) and contains 8468 individuals from the 2003 WHS and 7759 individuals from the 2007 SAGE survey.

While the SAGE survey is more detailed and comprehensive, both the WHS and SAGE surveys contain information on various individual and household characteristics for individuals older than 18 including age, marital status, household consumption and assets, and anthropometrics. In addition, the surveys include questionnaires on various physical and mental health outcomes. We use several different measures of psychological well-being. First, we study the presence of key depression symptoms. In both surveys, respondents are asked if they felt sad, lost interest or lacked energy for more than two weeks in the last 12 months. We use an indicator for having all three key depression symptoms as our measure of mental distress. Further, we examine agency, the feeling of being able to control the important things in life, and stress. Our measures of stress are based on self-reported cognitive and sleep difficulties and the feeling of being unable to cope with all the things that they have to do.

Table 1 presents descriptive statistics on the demographic characteristics and psychological well-being outcomes for individuals by survey wave.

Individuals in 2007 are significantly less likely to have all three of the key depression symptoms (7% vs. 11%, p-value < 0.001) and cognitive difficulties (11% vs 16%, p-value < 0.001), yet they are more likely to report sleep difficulties (10% vs. 9.5%, p-value = 0.045), and not being able to control the important things in life (18% vs. 13%, p-value < 0.001) or cope with everything they need to do (20% vs. 18%, p-value = 0.001). Differences in mental health outcomes over time could be due to changes in the composition of the sample because of the different survey methodology used

Table 1
Descriptive statistics by year.

	WHS (2003)	SAGE (2007)	p value
Outcomes			
Depressive symptoms	0.11	0.07	<0.001
Cognitive difficulties	0.16	0.11	<0.001
Sleep difficulties	0.095	0.1	0.045
Cannot cope	0.18	0.2	0.001
Cannot control	0.13	0.18	<0.001
Demographics			
Age 18–30	0.36	0.21	<0.001
Age 30–40	0.29	0.22	<0.001
Age 40–50	0.2	0.18	<0.001
Age 50+	0.14	0.39	<0.001
Yrs educ-none	0.35	0.4	<0.001
Yrs educ 1–4	0.08	0.09	0.718
Yrs educ 5–7	0.15	0.16	0.786
Yrs educ 8–11	0.05	0.01	<0.001
Yrs educ ≥12	0.37	0.34	0.001
Female	0.52	0.68	<0.001
Married	0.79	0.83	<0.001
Single	0.16	0.09	<0.001
Widowed	0.05	0.08	<0.001
Household has electricity	0.68	0.69	0.043
Household has phone	0.15	0.44	<0.001
Household has a bike or motorbike	0.64	0.69	<0.001
Total monthly per capita expenditures (pce)	734.16	708.78	0.197
Monthly food per capita expenditures (pce)	374.26	504.59	<0.001
Servings of fruit and vegetables	3.56	2.95	<0.001
Household Size	6	6.18	<0.001
Interview Month – February	0.05	0	<0.001
Interview Month – March	0.39	0	<0.001
Interview Month – April	0.47	0.08	<0.001
Interview Month – May	0.09	0.38	<0.001
Interview Month – June	0	0.38	<0.001
Interview Month – July	0	0.15	<0.001
Number of observations	8468	7759	

Notes: [1] The table shows means for continuous variables and proportions for discrete variables. [2] Sample is restricted to adults between the age of 18 and 60 living in primary sampling units surveyed in both years.

in the WHS and SAGE surveys. For example, respondents in 2007 are older (39% are above 50 compared to 14% in 2003) and less educated (40% of the 2007 sample have no education compared to 35% in 2003). There are more female respondents in 2007 compared to 2003 (68% vs. 52%) and more respondents who are married. Individuals are more likely to live in larger households that have electricity, phone and bike or motorbike in 2007 than in 2003.

Demographic and socio-economic control variables have been shown to be important predictors of mental health in low and middle-income countries (Arokiasamy et al., 2015; Patel et al., 1999; Poongothai, Pradeepa, Ganesan, & Mohan, 2009). Consistent with prior research, we find that age is a key determinant of psychological well-being and older individuals have worse outcomes (Appendix Table 1). Prior work also shows married individuals in India have lower incidence of depression than those who are divorced or widowed (Poongothai et al., 2009), our sample also demonstrates this. Similar to the findings of Poongothai et al. (2009) and Patel et al. (1999), females are more likely than males to report depression symptoms as well as cognitive and sleep difficulties. Low income and poverty are associated with increased mental health disorders, as are low education levels, likely because higher education is generally associated with higher socio-economic status (Patel et al., 1999; Poongothai et al., 2009). Appendix Table 1 demonstrates that survey respondents living in households with electricity or assets such as phone or bike/motorbike are generally less likely to experience mental health problems. Because mental health is influenced by these factors, we control for demographic characteristics in all regressions estimating the effect of temperature and rainfall fluctuations on psychological well-being.

2.2. Climate data

We merge the WHS and SAGE survey data to climate data using GPS coordinates for each psu, available from the WHS survey. We use average monthly temperature (°C) and total monthly precipitation (mm) from the most recent version (v4.01, 2015) of the gridded, 0.5×0.5 degree Matsurra & Willmott series (Wilmott & Matsuura, 2001). Given their extensive geographic and temporal coverage, these data are commonly used to explore climate-economy dynamics (Dell, Jones, & Olken, 2014). However, one disadvantage of the data is that daily fluctuations in temperature and precipitation are masked in monthly averages and totals. This makes it difficult to identify immediate effects of extreme temperatures on psychological well-being, such as increased aggression on hot days, but could capture lagged effects.

To estimate the effect of weather variability on psychological well-being, we use relative measures of extreme temperature and precipitation similar to the standard deviation adjusted approaches described in Dell et al. (2014). Our measures of temperature anomalies are defined as the number of months during the previous calendar year that had a temperature of more than one standard deviation (SD) above[2] the 30-year psu-level average for that month, also used in Burgess et al. (2014) and Hsiang et al. (2013). The long-run monthly average is based on temperature observations from 1970 to 1999. Similarly, our measures of rainfall shocks are defined as the number of months with precipitation of more than one SD below the long-run monthly average, as in Iyer and Topalova (2014). [3]As a robustness check, we also use an absolute measure of a temperature shock. Prior research has shown that temperatures above 32 degrees Celsius have a harmful effect on crop yields (Deschenes & Greenstone, 2007). Thus, we calculate the number of months in the previous calendar year with mean temperature above the threshold of 32 degrees Celsius.[4]

Table 2 presents summary statistics for temperature and precipitation anomalies for the year prior to the survey year.[5]

The number of months with temperatures greater than one SD above the long-run average (hot months) is significantly higher in 2002 than in 2006 (4.03 vs. 3.17, p-value < 0.001), and there were an average of 1.24 and 0.69 months with mean monthly temperature higher than 32 degrees Celsius in 2002 and 2006, respectively (p-value < 0.001). Precipitation anomalies were also significantly different between 2002 and 2006; 2002 had significantly more dry months (1.46 vs. 1.11, p-value < 0.001). The temporal variation in extreme temperatures is also evident from Fig. 1, which shows

[2] We focus on studying the effect of unusually hot months only. Measures used to examine health effects of cold weather generally use temperatures that fall below 8 degrees Celsius; observed average monthly temperatures from 1970 to 2006 do not fall below 11 degrees Celsius, so relatively cold months are not likely cold enough to have a significant effect on physical or psychological well-being. We thus exclude measures of cold weather from the results.

[3] In this paper we focus on drought conditions as our main measure of precipitation anomalies since previous literature has shown that drought has significant effects on mental distress (Carroll et al., 2009; Chemin et al., 2013) .The results for abnormally high precipitation are similar and are available from the authors by request.

[4] Given the absolute nature of this measure, in all regressions using this measure we also control for the 30-year temperature mean and standard deviation, calculated by first obtaining the average temperature and standard deviation for each individual month in a given psu during the 30-year period, and then averaging the 30-year monthly averages to calculate the overall temperature mean and standard deviation.

[5] The temperature fluctuations in the SAGE districts are representative of the six states surveyed. Those account for about 570 million people, or 43% of the Indian population.

Table 2
Climate statistics.

	2002	2006	p value
Number of months with temperature > 1SD above long-run monthly average (hot months)	4.03 (2.59)	3.17 (1.84)	<0.001
Number of months with temperature > 32degrees C	1.24 (1.42)	0.69 (0.98)	<0.001
Number of months with precipitation > 1SD below long-run monthly average (dry months)	1.46 (0.96)	1.11 (1.14)	<0.001
Number of primary sampling units (psus)	371	371	

Notes: [1] The table shows means with standard deviations in parentheses. [2] Sample is restricted to primary sampling units surveyed in both years.

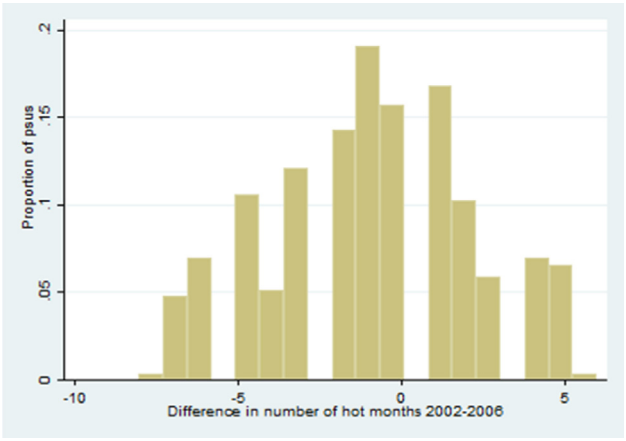

Fig. 1. Difference in number of hot months between 2002 and 2006. Source: Authors' calculations using the Willmott and Matsuura monthly time series data, http://climate.geog.udel.edu/~climate/html_pages/README.ghcn_ts2.html.

the distribution of the difference in number of hot months between 2002 and 2006 at the psu level.

In addition to temporal variation in extreme temperature and precipitation, there is also spatial variation. The large standard deviations in Table 2 indicate that both temperature and precipitation anomalies vary substantially across psus. Fig. 2 further illustrates this point. In 2002, psus with a higher number of hot months were concentrated in the west and north-west of the country, while psus in the north and north-east experienced fewer hot months. In 2006, psus in the north and north-east experienced more hot months than those in the west and north-west.

Next, we present our empirical specification which takes advantage of this temporal and spatial variation in weather.

3. Empirical specification

In order to study the effect of weather on psychological well-being, we estimate the following generalized difference-in-differences model for outcome y of individual i living in primary sampling unit (psu) k at time t:

$$y_{i,k,t} = \alpha + \beta_1 Weather_{k,t} + \beta_2 Time_t + \beta_3 \eta_k + \rho X_{i,k,t} + \epsilon_{i,k,t}$$

where $Weather_{k,t}$ is our temperature or rainfall measure defined at the psu level. We also include an indicator for an observation from the 2007 survey, $Time_t$, and psu fixed effects, η_k. Standard errors are clustered at the psu level. Since outcomes are observed at the individual level, while weather shocks are at the psu level, we also control for individual characteristics, $X_{i,k,t}$. These include the variables specified in Table 1: dummy variables for age categories 31–40, 41–50 and older than 50 (omitted category is 18–30); dummy variables for four or less years of education, and 5–7, 8–11, and 12 or more years of education (omitted category is "no education"); indicators for single and widowed marital status (omitted category "married"); household size; presence of electricity; and household assets (phone and bike or moped).

To identify the effect of weather fluctuations on mental health, we include psu fixed effects which control for time-invariant psu characteristics, such as geography, that may be correlated both with weather shocks and mental health. We also control for year fixed effects to account for changes in country-wide economic, policy or health phenomena. In addition, we include month-of-interview fixed effects to control for the effect current temperatures may have on mental health and for the difference in time passed since the end of the previous calendar year.

Our identification strategy relies on the absence of time-varying unobservable characteristics that are correlated both with weather and psychological well-being.[6] For example, migration driven by short-run climate shocks or long-run climate risk could bias estimates if only healthy people or those most distressed by weather shocks migrate. Yet, migration in India is very low. Imbert and Papp (2015) find that only 0.4% of rural adults in India report having migrated in the past year from one rural area to another and about 1.9% of adults migrate from rural to urban areas. It is unclear what proportion of migration is due to weather shocks but overall migration appears to be low. Further evidence is provided by Dallmann and Millock (2016) who study climate variability and inter-state migration in India, and demonstrate that the magnitude and duration of a drought episode preceding migration does not serve as a push factor although the frequency of drought episodes slightly increases migration probability (an additional drought episode in a five-year period is associated with 1.6% higher probability of migration). Thus, while some migration may result from weather shocks, we believe the effects of this are minimal and it is not a significant source of bias.

Finally, the coefficient estimates would be biased if there is selective attrition or mortality, affecting the sample composition in the two survey waves. Table 1 shows that the population samples in the two years are significantly different on various demographic dimensions due to changes in the sampling methodology between the WHS and SAGE surveys. As a robustness check, we use the sample of 3527 individuals common to both surveys to estimate a model that replaces psu fixed effects with individual fixed effects to confirm our results are not driven by differences between the two samples.

4. Results

4.1. Main results: the effect of climate shocks in the past year

Table 3 presents results of the main specification testing the effect of climate shocks in the past year on psychological well-being. Each coefficient comes from a separate regression.

We find that an additional month of unusually high temperatures in the last year has a significant adverse effect on cognition, sleep, ability to cope and ability to control important things in life. Specifically, it is associated with a 0.8 percentage point greater likelihood of experiencing cognitive difficulties, 0.58 percentage point greater likelihood of difficulty sleeping, and 0.67 and 1.1

[6] The main identification assumption in the difference-in-differences model is the assumption of common trends so that any difference between observations that experience a weather shock and those that do not is due to the weather shock only and not to differential changes in time-varying unobservable characteristics. While this assumption is not directly testable, we examine whether it is likely to hold by including leads of the weather variables and testing if future weather is a significant predictor of current outcomes (it should not be). We find that generally it isn't.

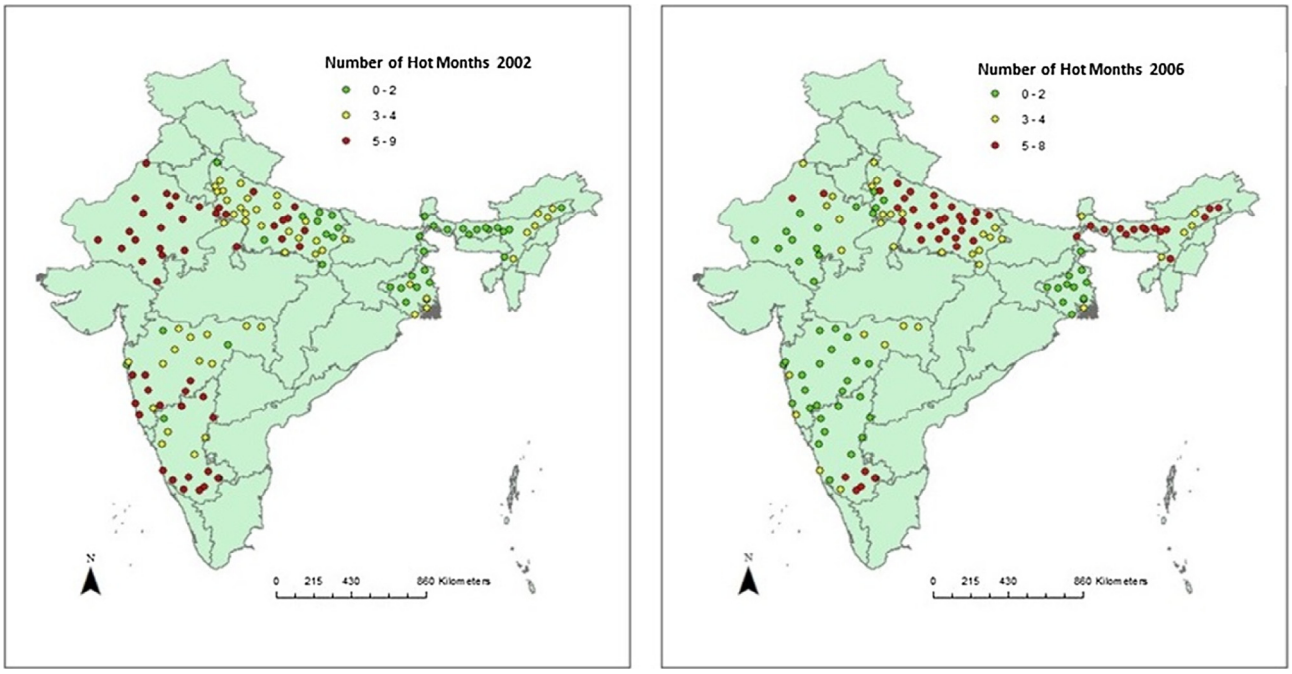

Fig. 2. Geographical distribution of hot months. Source: Authors' calculations using the Willmott and Matsuura monthly time series data, http://climate.geog.udel.edu/~climate/html_pages/README.ghcn_ts2.html.

Table 3
The effects of extreme temperature and precipitation in the previous year.

	Key depression symptoms (1)	Cognitive difficulties (2)	Sleep difficulties (3)	Cannot cope (4)	Cannot control (5)
Model with individual temperature effects					
Number of hot months	0.0027	0.0080**	0.0058**	0.0067**	0.0110**
	(0.0023)	(0.0028)	(0.0022)	(0.0031)	(0.0027)
Model with individual precipitation effects					
Number of dry months	0.0017	0.0095*	0.0065	0.0098	0.0212**
	(0.0060)	(0.0056)	(0.0052)	(0.0072)	(0.0069)
Model with combined temperature and precipitation effects					
Number of hot months	0.0036	0.0087**	0.0064**	0.0065*	0.0086**
	(0.0029)	(0.0033)	(0.0027)	(0.0038)	(0.0032)
Number of dry months	−0.0034	−0.0028	−0.0025	0.0006	0.009
	(0.0075)	(0.0064)	(0.0060)	(0.0086)	(0.0082)

Notes: [1] Each model presents a different regression, controlling for psu and year fixed effects, as well as individual and household characteristics. [2] Standard errors, clustered at the psu level, in parentheses. [3] * denotes significance at the 10% level, ** denotes significance at the 5% level.

percentage points higher likelihood of feeling unable to cope or control the important things in life, all significant at the 5% level. The number of hot months has a positive, but not significant impact on depression symptoms. These results are robust to using an alternate, absolute temperature measure – the number of months with mean temperature above 32 degrees Celsius (Appendix Table 2), and robust to limiting the sample to individuals common to both surveys and replacing psu fixed effects with individual fixed effects (Appendix Table 3).

Our findings are consistent with other work that examines climate effects on psychological well-being. Hot weather has previously been associated with increased suicide rates, and hospital admissions for schizophrenia and bipolar disorder (Kim, Kim, & Kim, 2011; Sung, Chen, Lin, Lung, & Su, 2011; Sung, Chen, & Su, 2013). This work, and prior research in general, examines the effect of daily temperatures on mental distress and thus provides support for the short-term effect of heat on mental health. Our study captures the long-term effect of weather anomalies on psychological well-being, similar to Carleton (2017) who shows that higher temperatures during the growing season are associated with an increase in annual suicide rates in India.

Next we present the results for the effect of drought on mental health. We find that dry weather increases mental distress, although results are only significant for cognitive difficulties (at the 10% level) and inability to control the important things in life. Again, these findings support previous research; Carroll et al. (2009) find that drought during the growing season is associated with reduced life satisfaction among rural Australians. Chemin et al. (2013) study the effect of abnormally low precipitation in the 12 months before the survey and find it is associated with increased stress levels among Kenyan farmers.

India hosts a wide variety of climates, given its large size, yet the onset of the rainy season also tends to bring cooler temperatures across the country (Fig. 3).

Therefore, we also explore specifications that control both for the number of hot and the number of dry months. Overall, the

effects of hot conditions are similar in specifications that include or exclude the effects of extreme precipitation. Controlling for number of hot months, we find that the number of dry months has no significant effect on psychological well-being. These results suggest that while there is some correlation between temperature and precipitation, the effects of climate on psychological well-being are driven largely by extreme temperatures and not precipitation. We thus focus on studying the effects of hot months for the remainder of the analysis.

4.2. Heterogeneity by rural-urban area of residence

Next, we examine heterogeneities in the effects of extreme weather among rural and urban populations. Panel A in Table 4 shows that rural populations experience consistently negative effects of hot temperatures on psychological well-being and the effects are larger compared to the full sample: an additional hot month in the prior calendar year is associated with a 0.99 percentage point greater likelihood of experiencing cognitive difficulties, 0.7 percentage point greater likelihood of difficulty sleeping, and 0.74 and 1.28 percentage points higher likelihood of feeling unable to cope with or control the important things in life, all significant at the 5% level. Controlling for precipitation, we find that hot weather has a significant effect on increasing depression symptoms as well.

Urban populations, on the other hand, are generally not affected by extreme temperature fluctuations (Panel B, Table 4). These results suggest that effects of climate are disproportionately felt among rural populations. This finding implies that the main mechanism through which temperature affects psychological well-being is not through physiological effects of extreme weather, which should similarly influence rural and urban populations. While we cannot reject the influence of physiological effects, because urban populations may have greater access to adaptation mechanisms (such as access to cooling fans and flexible work schedules), below we provide evidence to support the hypothesis that the main channel is the change in socio-economic conditions that agriculture-based rural populations in India face as a result of weather shocks.

5. Mechanisms

5.1. Weather shocks and agriculture

We perform two tests to examine whether agricultural productivity is the mechanism underlying the relationship between extreme weather and psychological well-being for rural households. First, we divide the one-year weather measure into two periods: the primary agricultural (Kharif) season and the period outside the primary agricultural season. The Kharif agricultural season takes place in the second half of the year, roughly between July and December, which coincides with India's monsoon season, and is the period when main staple crops such as rice, corn and millet are grown. The results for rural households, presented in Panel A of Table 5, show a significant adverse effect of agriculture-season temperatures on depression symptoms, and sleep and cognitive difficulties, robust to including controls for precipitation. In the months outside of the agricultural season, heat generally does not have a significant adverse effect on psychological well-being once we control for abnormally low precipitation (with the exception of the inability to control the important things in life).

These findings are consistent with Carleton (2017) who shows that an increase in temperature during the growing season increases India's annual suicide rate, but an increase in temperature during the nongrowing season has no effect on suicides. As a placebo test, we also analyze the effect of agricultural season

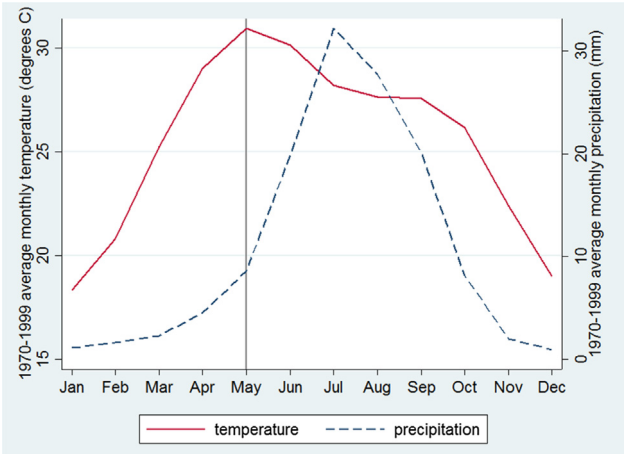

Fig. 3. Distribution of average monthly temperature and precipitation. Source: Authors' calculations using the Willmott and Matsuura monthly time series data, http://climate.geog.udel.edu/~climate/html_pages/README.ghcn_ts2.html.

weather anomalies among urban populations and find that there is no significant negative effect of temperature or precipitation on mental health (Panel B, Table 5).

Second, we test whether heat shocks during the agricultural season are indeed associated with lower agricultural output. Because the surveys don't contain information on agricultural production, we use district-level information on crop yields by year and season[7] for the 2002 and 2006 agricultural seasons. Appendix Table 4 presents summary statistics for the yield (in tons per hectare) of the four most prevalent Kharif crops – millet, rice, maize and sorghum. Average yields for all crops but sorghum increased between 2002 and 2006, although the increase in rice yield was not statistically significant. Next, we use a district fixed effects regression model to examine how changes in the yields of these crops were affected by temperature and rainfall fluctuations, while accounting for time-invariant district characteristics, such as geography, that may affect both yield and temperatures. We additionally control for the time difference to account for any country-wide technological changes between 2002 and 2006. In Table 6, we show that as the number of months of unusually high agricultural-season temperatures increases, the yields of millet, rice, and sorghum decrease, even when accounting for unusual precipitation. The effect of temperature shocks on maize yields is also negative but is not statistically significant.

We further test whether lower agricultural production is the mechanism by which weather shocks influence psychological well-being by including controls for crop production in the main regression model. Since crop production varies at the district level, we use district fixed effects in this model. Indeed, the size of the effect of hot temperatures on psychological well-being (with the exception of the outcome of "cannot control") is reduced when we control for agricultural production (Appendix Table 5).

5.2. Weather shocks and consumption

The results thus far suggest that temperature fluctuations during the prior agricultural season are associated with worse psychological well-being in the following months, and these effects are partially explained by temperature shocks affecting agricultural

[7] Data available at: https://data.gov.in/catalog/district-wise-season-wise-crop-production-statistics.

Table 4
Heterogeneity by rural–urban area of residence.

	Key depression symptoms (1)	Cognitive difficulties (2)	Sleep difficulties (3)	Cannot cope (4)	Cannot control (5)
Panel A: Rural populations					
Base model					
Number of hot months	0.0033	0.0099**	0.0070**	0.0074**	0.0128**
	(0.0025)	(0.0032)	(0.0024)	(0.0036)	(0.0031)
Model controlling for dry months					
Number of hot months	0.0059**	0.0099**	0.0082**	0.0080*	0.0114**
	(0.0029)	(0.0037)	(0.0027)	(0.0042)	(0.0034)
Panel B: Urban populations					
Base model					
Number of hot months	−0.0016	−0.0042	−0.0008	−0.0022	−0.0022
	(0.0053)	(0.0045)	(0.0052)	(0.0082)	(0.0085)
Model controlling for dry months					
Number of hot months	−0.0158*	−0.0047	−0.0088	−0.0117	−0.0152
	(0.0093)	(0.0069)	(0.0080)	(0.0128)	(0.0139)

Notes: [1] Table shows two different regressions specifications – with and without controls for precipitation. All regressions control for psu and year fixed effects, as well as household and individual characteristics. [2] Standard errors, clustered at the psu level, in parentheses. [3] * denotes significance at the 10% level, ** denotes significance at the 5% level.

Table 5
The effect of weather fluctuations on rural populations by season.

	Key Depression symptoms (1)	Cognitive difficulties (2)	Sleep difficulties (3)	Cannot cope (4)	Cannot control (5)
Panel A: Rural populations					
Base model					
Number of hot months agricultural season	0.0121**	0.0153**	0.0131**	0.003	0.0065
	(0.0037)	(0.0049)	(0.0036)	(0.0058)	(0.0050)
Number of hot months off-agricultural season	−0.0128**	0	−0.0042	0.0156*	0.0243**
	(0.0063)	(0.0054)	(0.0049)	(0.0091)	(0.0083)
Model controlling for dry months					
Number of hot months agricultural season	0.0138**	0.0150**	0.0138**	0.0071	0.0058
	(0.0040)	(0.0050)	(0.0037)	(0.0058)	(0.0053)
Number of hot months off-agricultural season	−0.0106	−0.001	−0.0028	0.0018	0.0259**
	(0.0065)	(0.0062)	(0.0053)	(0.0097)	(0.0085)
Panel B: Urban populations					
Base model					
Number of hot months agricultural season	0.0067	−0.0021	−0.001	−0.0071	−0.0123
	(0.0073)	(0.0065)	(0.0076)	(0.0117)	(0.0125)
Number of hot months off-agricultural season	−0.0145	−0.0076	−0.0005	0.0053	0.0135
	(0.0100)	(0.0062)	(0.0074)	(0.0143)	(0.0159)
Model controlling for dry months					
Number of hot months agricultural season	−0.0063	−0.0021	−0.0084	−0.0073	−0.0234
	(0.0085)	(0.0079)	(0.0089)	(0.0115)	(0.0153)
Number of hot months off-agricultural season	−0.0349**	−0.0107	−0.0105	0.0009	−0.0044
	(0.0135)	(0.0087)	(0.0109)	(0.0168)	(0.0187)

Notes: [1] Table shows two different regressions specifications – with and without controls for precipitation. All regressions control for psu and year fixed effects, as well as household and individual characteristics. [2] Agricultural season defined as July to December. [3] Standard errors, clustered at the psu level, in parentheses. [4] * denotes significance at the 10% level, ** denotes significance at the 5% level.

Table 6
The effect of weather shocks during the prior agricultural season on agricultural yields.

	Bajra (Millet) (1)	Rice (2)	Maize (3)	Jowar (Sorghum) (4)
Base model				
Number of hot months agricultural season	−0.0483**	−0.0683**	−0.0083	−0.0959**
	(0.0195)	(0.0170)	(0.0257)	(0.0414)
Model controlling for dry months				
Number of hot months agricultural season	−0.0582**	−0.0823**	−0.0051	−0.1533**
	(0.0250)	(0.0210)	(0.0314)	(0.0492)

Notes: [1] Table shows two different regressions specifications – with and without controls for precipitation. All regressions control for district and year fixed effects. [2] Agricultural season defined as July to December. [3] Standard errors in parentheses. [4] * denotes significance at the 10% level, ** denotes significance at the 5% level.

output. Decreased agricultural productivity may result in lower household income. While farmers can use various strategies to cope with an adverse income shock, consumption smoothing may be incomplete. Jacoby and Skoufias (1997) present evidence that financial market imperfections in rural India reduce household ability to borrow against future income. Even if rural households are able to smooth consumption, they may do so at the cost of selling productive assets which may reduce financial security in the future (Rosenzweig & Wolpin, 1993).

If households are able to completely smooth consumption after the negative income shock, then the negative psychological effects we see could be associated with stress resulting from greater financial insecurity. If they are not able to fully smooth consumption, the mental health effects could be due to both decreased consumption and greater financial insecurity. If consumption is affected by weather shocks, we would expect that physical health will also be affected because people reduce calorie intake and/or reduce health expenditures (which is one potential mechanism through which lower consumption could indirectly affect mental health).

The data does not allow us to test directly the effect of climate shocks on household income or specifically, agricultural income. Instead, we examine the effect of agricultural season weather fluctuations on rural populations' consumption. We find that unusually hot weather is associated with higher total per capita expenditures, which could be due to price increases in communities hit hardest by weather shocks (Table 7). This effect is small. An additional hot month is associated with 15 Rps higher total per capita expenditure, while mean per capita expenditures in 2002 are 734 Rps. These results are not robust to specifications that control for drought conditions. The effect on food expenditures is negative, but not significant. We find a significant negative effect of high temperature on daily consumption of fruit and vegetables.[8] Since consumption and expenditure data may be prone to measurement and reporting error, we also examine the probability of being underweight (BMI < 18) and reporting bad health. We find that an additional hot month in the prior agricultural season is associated with a 2.91 percentage point higher probability of being underweight and 2.38 percentage point higher probability of reporting bad health. These results provide suggestive evidence that the effect of weather shocks on psychological well-being is likely driven not only by financial insecurity, but also by lower consumption.

6. The potential of poverty alleviation programs for mitigating the adverse climate change effects

One year prior to the 2007 wave of the SAGE survey, India began implementing the National Rural Employment Guarantee Scheme (NREGS), providing each rural household with 100 days of low-skilled work in public works projects. The program aimed to improve rural infrastructure as well as insure rural households against negative income shocks. It was first introduced in February 2006 to 200 of the poorest rural districts in India. The second phase of the program expanded access to 130 additional districts in April 2007. A year later, the program was made available to all remaining districts. Out of 127 districts in our rural sample, 35 receive NREGS in the first phase of program implementation, before the start of the 2007 SAGE survey. The timing of NREGS provides an opportunity to examine whether climate effects on psychological well-being may be mitigated by public policies and programs designed to cushion income shocks among rural populations. We examine the effect of NREGS participation by modifying the main specification to include a variable for NREGS receipt in 2007, and its interaction with the number of hot months. The coefficient on the NREGS receipt variable shows how district availability of NREGS affected mental health outcomes of rural residents. The coefficient on the interaction term between number of hot months and NREGS receipt shows to what extent the program affected their vulnerability to hot weather.

Results in Table 8 show that the main coefficient of interest, the interaction term between weather anomalies and NREGS receipt, is negative for all mental health outcomes, although only significant for cognitive and sleep difficulties. This suggests that program availability mitigated some of the negative effects of hot weather anomalies on mental health. For example, an additional hot month is associated with a 1.83 percentage point increase in the probability of cognitive difficulties and 1.42 percentage point increase in probability of sleep difficulties in the absence of the program. On the other hand, an additional hot month is associated with a 1.28 and 1.44 percentage point *decrease* in the probability of cognitive and sleep difficulties, respectively, for residents of districts that received the program. The results are robust to controlling for number of extreme dry months.

We should be cautious when interpreting these results as causal. The coefficient on NREGS receipt shows that the program is associated with a significantly higher probability of residents reporting they are unable to cope with life and control the important things in life. This is consistent with the program being implemented in poorer districts with worsening mental health outcomes. Program placement would bias the coefficient of interest only if districts were given priority based on the weather shocks they experienced. While the algorithm for district participation in NREGS is not publicly available, previous studies suggest selection into the program is determined using a development ranking by the Indian Planning Commission (Bose, 2017; Khanna & Zimmermann, 2017). The rank is based on three indices – proportion of Scheduled Caste and Scheduled Tribe population as of the 1991 census, agricultural wages (1996–1997), and output per agricultural worker (1990–1993) – past measures which are not likely to be correlated with current weather anomalies.

To test whether program participation is affected by weather anomalies, we create a district-level indicator for weather anomalies in the 2002 and 2006 agricultural seasons by taking the mean number of hot months across the district psus.[9] We then regress NREGS receipt on district-level measures of number of hot months during the 2002 and 2006 agricultural seasons, as well as the difference in the number of hot months between the two years (restricting the sample to districts with available district controls) (Appendix Table 6). We find that a higher number of hot months in the 2002 agricultural season is associated with lower probability of the district receiving NREGS in Phase 1. However, when we control for district characteristics including the three indices underlying the development ranking, the significant relationship between number of hot months and NREGS receipt disappears. Further, there is no

[8] One caveat of this analysis, however, is that households were asked different questions on consumption in both years and while we attempt to standardize the answers, some of those differences or measurement errors may affect the results. For example, in 2003, households were asked for total monthly spending in the last four weeks, while in 2007, they were asked about usual monthly spending. The question on food spending also differed between the survey waves: in 2003, households reported food spending in the last four weeks while in 2007, they were only asked about food spending in the last seven days, which we then extrapolated to four weeks. While the question on servings of fruit and vegetables is consistent across survey waves, it is hard to know if the lower number of servings of fruits and vegetables is due to households switching to other foods or households cutting down on food overall because they are unable to meet their consumption needs.

[9] The mean number of psus per district in our data is 2.73. The median is 2.

Table 7
The effect of weather shocks during the prior agricultural season on consumption among rural populations.

	Per capita total expenditures (1)	Per capita food expenditures (2)	Servings of fruit and vegetables (3)	Underweight (BMI < 18) (4)	Reports bad health (5)
Base model					
Number of hot months agricultural season	14.8956**	−0.3916	−0.2049**	0.0291**	0.0238**
	(6.7824)	(2.6232)	(0.0450)	(0.0049)	(0.0036)
Model controlling for dry months					
Number of hot months agricultural season	13.0522	−0.7595	−0.1685**	0.0315**	0.0265**
	(8.5017)	(3.0997)	(0.0501)	(0.0056)	(0.0040)

Notes: [1] Table shows two different regressions specifications – with and without controls for precipitation. All regressions control for psu and year fixed effects, as well as household and individual characteristics. [2] Sample restricted to rural populations only; Agricultural season defined as July to December. [3] Standard errors, clustered at the psu level, in parentheses. [4] * denotes significance at the 10% level, ** denotes significance at the 5% level.

Table 8
The effect of NREGS on insuring rural populations against agricultural season weather shocks.

	Depression symptoms (1)	Cognitive difficulties (2)	Sleep difficulties (3)	Cannot cope (4)	Cannot control (5)
Base model					
Number of hot months agricultural season	0.0074**	0.0183**	0.0142**	0.0077	0.0156**
	(0.0036)	(0.0049)	(0.0035)	(0.0055)	(0.0047)
Number of hot months agricultural season * NREGS receipt	−0.0056	−0.0311**	−0.0286**	−0.0311	−0.0348
	(0.0122)	(0.0139)	(0.0120)	(0.0197)	(0.0230)
NREGS receipt	0.0451	0.045	0.0507*	0.1180**	0.0854*
	(0.0313)	(0.0379)	(0.0286)	(0.0476)	(0.0487)
Model controlling for dry months					
Number of hot months agricultural season	0.0099**	0.0169**	0.0150**	0.0082	0.0142**
	(0.0039)	(0.0051)	(0.0035)	(0.0059)	(0.0050)
Number of hot months agricultural season * NREGS receipt	−0.0033	−0.0324**	−0.0277**	−0.0307	−0.036
	(0.0121)	(0.0141)	(0.0124)	(0.0202)	(0.0235)
NREGS receipt	0.0416	0.0471	0.0495*	0.1173**	0.0874*
	(0.0308)	(0.0377)	(0.0288)	(0.0481)	(0.0492)

Notes: [1] Table shows two different regressions specifications – with and without controls for precipitation. All regressions control for psu and year fixed effects, as well as household and individual characteristics. [2] Sample restricted to rural populations only; Agricultural season defined as July to December. [3] Standard errors, clustered at the psu level, in parentheses. [4] * denotes significance at the 10% level, ** denotes significance at the 5% level.

significant relationship between the change in weather anomalies between 2002 and 2006 and NREGS receipt.

Overall, we believe these results provide at least suggestive evidence for the effectiveness of poverty alleviation programs in mitigating the adverse mental health effects of climate variability.

7. Conclusion

The adverse impacts of climate change on rural, agriculture-based economies are likely to increase over time and are thus of great concern. In this paper, we study the effects of climate change on the psychological well-being of Indian adults and show that higher temperatures have a significant deleterious effect on stress (proxied by sleep, ability to cope and cognitive difficulties) and lack of agency (being able to control the important things in life) among individuals in rural, but not urban, areas. The results are robust to controlling for extremely dry conditions. We provide suggestive evidence that the adverse effects of extreme heat are partly due to reductions in agricultural output, which, in turn, reduce income and consumption. We further test the potential of programs like the National Rural Employment Guarantee Scheme – a workfare program - to insure rural populations against climate-induced income shocks and associated mental distress and find encouraging results. Given that nearly half of the global population lives in rural areas, understanding the effects of climate on psychological well-being and identifying potential resolutions is critical for insuring vulnerable populations. Increasingly hot climates will lead to even greater deviations from current temperatures and, in the absence of mitigation or adaptation, will likely have increasingly adverse effects on mental health.

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Appendix

See Appendix Tables 1–6

Appendix Table 1
Determinants of Mental Health.

	Key depression symptoms (1)	Cognitive difficulties (2)	Sleep difficulties (3)	Cannot cope (4)	Cannot control (5)
Age 31–40	0.0288**	0.0292**	0.0295**	0.0518**	0.0348**
	(0.0070)	(0.0076)	(0.0062)	(0.0093)	(0.0087)
Age 41–50	0.0483**	0.0709**	0.0613**	0.0466**	0.0313**
	(0.0077)	(0.0093)	(0.0081)	(0.0104)	(0.0096)
Age ≥50	0.0620**	0.1216**	0.0890**	0.0500**	0.0348**
	(0.0085)	(0.0106)	(0.0086)	(0.0104)	(0.0098)
Years of Education ≤4	0.0037	−0.0352**	−0.0017	0.0003	−0.0223
	(0.0097)	(0.0118)	(0.0112)	(0.0144)	(0.0140)
Years of education 5–8	−0.0160**	−0.0508**	−0.0271**	−0.0267**	−0.0337**
	(0.0081)	(0.0092)	(0.0082)	(0.0105)	(0.0101)
Years of education 8–12	0.0126	−0.0516**	−0.0286	0.0178	−0.0231
	(0.0169)	(0.0178)	(0.0175)	(0.0198)	(0.0189)
Years of education ≥12	−0.0337**	−0.0872**	−0.0387**	−0.0284**	−0.0312**
	(0.0073)	(0.0083)	(0.0077)	(0.0097)	(0.0096)
Female	0.0214**	0.0558**	0.0300**	−0.0064	0.0016
	(0.0055)	(0.0066)	(0.0058)	(0.0080)	(0.0076)
Single	−0.0012	0.0194**	−0.0032	0.0026	0.0046
	(0.0070)	(0.0084)	(0.0064)	(0.0104)	(0.0098)
Widowed	0.0588**	0.0258*	0.0637**	0.0147	0.0264*
	(0.0138)	(0.0133)	(0.0142)	(0.0144)	(0.0144)
Household has electricity	−0.0258**	−0.0049	−0.0154**	−0.0309**	−0.0071
	(0.0076)	(0.0086)	(0.0071)	(0.0107)	(0.0092)
Household has a phone	−0.0108	−0.0152**	−0.0142**	−0.0386**	−0.0437**
	(0.0067)	(0.0071)	(0.0066)	(0.0086)	(0.0085)
Household has a bike or motorbike	−0.0152**	−0.006	−0.0093	−0.0261**	−0.0209**
	(0.0057)	(0.0071)	(0.0064)	(0.0085)	(0.0074)
Household size	−0.0011	0.0006	−0.0013	−0.0030**	−0.0016
	(0.0009)	(0.0011)	(0.0009)	(0.0012)	(0.0011)
Year = 2007	−0.0502**	−0.0869**	0.0155	−0.0141	0.0227
	(0.0197)	(0.0222)	(0.0186)	(0.0281)	(0.0283)
Constant	0.2539**	−1.2750**	−1.9083**	−2.6212**	0.5844**
	(0.0779)	(0.1062)	(0.0874)	(0.1388)	(0.1469)
psu FE	Yes	Yes	Yes	Yes	Yes
Month of Interview FE	Yes	Yes	Yes	Yes	Yes
Number of observations	15,127	15,377	15,369	15,234	15,235
Number of clusters	371	371	371	371	371

Notes: [1] Standard errors, clustered at the psu level, in parentheses. [2] * denotes significance at the 10% level, ** denotes significance at the 5% level.

Appendix Table 2
Robustness check using 32 degrees Celsius.

	Depression symptoms (1)	Cognitive difficulties (2)	Sleep difficulties (3)	Cannot cope (4)	Cannot control (5)
Base model					
Number of hot months	−0.0048	0.0400**	0.0160**	0.0435**	0.0427**
	(0.0090)	(0.0094)	(0.0079)	(0.0121)	(0.0131)
Model controlling for dry months					
Number of hot months	−0.0041	0.0462**	0.0198**	0.0502**	0.0541**
	(0.0091)	(0.0101)	(0.0084)	(0.0122)	(0.0122)

Notes: [1] Table shows two different regressions specifications – with and without controls for precipitation. All regressions control for psu and year fixed effects, as well as household and individual characteristics. [2] Standard errors, clustered at the psu level, in parentheses. [3] * denotes significance at the 10% level, ** denotes significance at the 5% level.

Appendix Table 3
Robustness check using individual fixed effects model.

	Key Depression symptoms (1)	Cognitive difficulties (2)	Sleep difficulties (3)	Cannot cope (4)	Cannot control (5)
Model with individual temperature effects					
Number of hot months	0.0070**	0.0124**	0.0116**	0.0112**	0.0094*
	(0.0030)	(0.0040)	(0.0034)	(0.0040)	(0.0048)
Model with individual precipitation effects					
Number of dry months	−0.0019	0.0126	0.0104	0.0193*	0.0137
	(0.0079)	(0.0096)	(0.0082)	(0.0105)	(0.0119)
Model with combined temperature and precipitation effects					
Number of hot months	0.0121**	0.0150**	0.0146**	0.0103**	0.0097
	(0.0038)	(0.0051)	(0.0042)	(0.0049)	(0.0062)
Number of dry months	−0.0203**	−0.0102	−0.0117	0.0037	−0.001
	(0.0095)	(0.0118)	(0.0094)	(0.0130)	(0.0151)

Notes: [1] Each number in this table comes from a different regression, controlling for individual and year fixed effects, as well as household and individual characteristics. [2] Standard errors, clustered at the psu level, in parentheses. [3] * denotes significance at the 10% level, ** denotes significance at the 5% level.

Appendix Table 4
Production statistics.

	2002	2006	p value
Bajra/Millet yield (tons per hectare)	0.79 (0.51)	0.99 (0.57)	0.02
Rice yield (tons per hectare)	1.83 (0.81)	1.97 (0.84)	0.20
Maize yield (tons per hectare)	1.27 (0.81)	1.61 (1.09)	0.01
Jowar/Sorghum yield (tons per hectare)	1.06 (1.13)	0.91 (0.51)	0.25

Notes: [1] The table shows means with standard deviations in parentheses. [2] Statistics for each crop are based on the sample of districts producing non-zero amounts of that crop between 2000 and 2006: 88, 119, 126, 95 for Bajra, Rice, Maize and Jowar respectively.

Appendix Table 5
The effect of weather fluctuations on rural populations by season.

	Key Depression symptoms		Cognitive difficulties		Sleep difficulties		Cannot cope		Cannot control	
	Main model with district FE (1)	Controlling for district production (2)	Main model with district FE (3)	Controlling for district production (4)	Main model with district FE (5)	Controlling for district production (6)	Main model with district FE (7)	Controlling for district production (8)	Main model with district FE (9)	Controlling for district production (10)
Base model										
Number of hot months agricultural season	0.0111** (0.0034)	0.0090** (0.0039)	0.0148** (0.0047)	0.0119** (0.0050)	0.0122** (0.0035)	0.0096** (0.0040)	0.0067 (0.0054)	0.0031 (0.0059)	0.0088* (0.0046)	0.0113** (0.0052)
Number of hot months off-agricultural season	−0.0084 (0.0057)	−0.0113** (0.0057)	−0.0006 (0.0051)	−0.001 (0.0050)	−0.003 (0.0044)	−0.0039 (0.0044)	0.0085 (0.0083)	0.0041 (0.0082)	0.0190** (0.0075)	0.0144** (0.0069)
Model controlling for dry months										
Number of hot months agricultural season	0.0120** (0.0037)	0.0098** (0.0042)	0.0150** (0.0047)	0.0115** (0.0050)	0.0135** (0.0034)	0.0108** (0.0040)	0.0068 (0.0057)	0.0027 (0.0063)	0.0079 (0.0049)	0.0104* (0.0055)
Number of hot months off-agricultural season	−0.0074 (0.0057)	−0.0110* (0.0056)	−0.0007 (0.0056)	−0.0018 (0.0055)	−0.0006 (0.0047)	−0.0022 (0.0046)	0.0097 (0.0084)	0.0043 (0.0083)	0.0191** (0.0077)	0.0145** (0.0072)

Notes: [1] Table shows two different regressions specifications – with and without controls for precipitation. All regressions control for district and year fixed effects, as well as household and individual characteristics. [2] Sample restricted to rural populations only; Agricultural season defined as July to December. [3] Standard errors, clustered at the psu level, in parentheses. [4] * denotes significance at the 10% level, ** denotes significance at the 5% level.

Appendix Table 6
Effects of weather shocks on NREGS receipt.

	NREGS receipt in Phase 1					
	(1)	(2)	(3)	(4)	(5)	(6)
Mean number of hot months in agricultural season of 2002	−0.0519** (0.0260)	−0.0162 (0.0219)				
Mean number of hot months in agricultural season of 2006			−0.0154 (0.0297)	−0.0297 (0.0243)		
Mean difference in number of hot months in 2002 and 2006					0.0211 (0.0194)	−0.005 (0.0172)
Controls	No	Yes	No	Yes	No	Yes
Number of districts	118	118	118	118	118	118

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